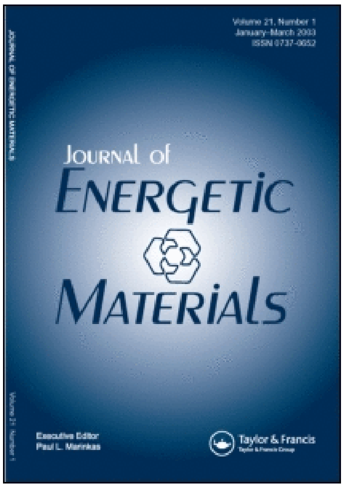

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THE APPLICATION OF NEURAL NETWORKS TO THE ASSESSMENT OF IMPACT TESTING ON EXPLOSIVES

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ABSTRACT

The BAM Fallhammer test is one of the most widely used impact tests, but the results of the test rely on the subjective assessments of the test operator using the senses of hearing, smell and sight. The paper describes an investigation into the suitability of using a neural network for determining the outcome of BAM Fallhammer tests. The network utilises digital data from instrumentation installed around the BAM apparatus, including a microphone and a gas sensor.

Selected examples are given to show that neural networks have the potential to distinguish between the test results of 'no reaction', 'decomposition', and 'explosion' for propellants, plastic and high explosives. The technique removes the possible operator dependence of assessments and the study in general may also lead to clarification of the categories involved in defining the test outcome.

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INTRODUCTION

The Classification of Explosives

Explosive materials have to be assessed so that necessary precautions can be taken for subsequent safe transport and storage, with each explosive being assigned a UN 'classification'. One of the properties of an explosive that is examined is its sensitiveness.

Sensitiveness has been defined as "the measure of the relative ease with which an explosive may be ignited or initiated by a particular stimulus" [1]. Stimuli can be both thermal and mechanical in nature, with mechanical stimuli being either in the form of friction or impact.

There are a number of tests that assess the behaviour of explosives when exposed to impact stimuli and the most common appear in the UN Tests and Criteria Manual (1995) [2]. The German BAM Fallhammer Test, named after the Bundesanstalt für Materialforschung und-prüfung Institute in Berlin, is probably the most widely used impact test, and has recently been chosen as the "recommended test" in the UN Manual.

The BAM Fallhammer Test

The principle of an impact test is simple. A mass is dropped from a known height on to a confined sample in order to determine the minimum energy input for reaction to occur. By varying the mass and the height, the energy input to the sample can be systematically altered until a value that indicates the sensitiveness of the explosive is determined.

The BAM Test applies a simple linear progression of steps until a mass and height combination provides an 'explosion'. The energy level immediately below is tested a further six times, and if no further 'explosion' occurs, the subsequent Limiting Impact Energy (LIE) is found.

The operator primarily uses the sense of hearing to detect an 'explosion' of the sample, with the senses of sight and smell confirming the result. Otherwise, the test drop is categorised as a 'no reaction'.

There is a third category accompanying the BAM test criteria, called 'decomposition'. This category was created in recognition of the fact that there remains the possibility that in some samples, the reaction is 'without flame or explosion (but) recognisable by change of colour or odour' [2]. This category is not treated as an 'explosion'.

The Problems with the BAM Fallhammer Test

Although widely used, the BAM method does have certain operational problems, some of which have been discussed previously, [3]:

i] On impact, the sample generally remains either chemically unchanged with no noise apart from that of the dropping weight, or is completely reacted by the process of explosion (accompanied with the subsequent production of noise and gas). Unfortunately, this is not always the case and quiet or partial explosions have been observed with a number of explosives.

There may also be some confusion concerning the reporting of these intermediate results as they are not dealt with satisfactorily by the current definition of 'decomposition'.

ii] Assessment of the test outcome depends on the subjective nature of the operator's senses of smell and hearing and a borderline case of an explosion may be missed. This subjectivity may also lead to differing conclusions between operators on witnessing the same test. Additionally, safety procedures demand that ear protection be worn and that a box surrounding the apparatus be closed whilst testing is in progress; these factors may impede the ability of the operator to determine the outcome of the test.

iii] There is no instrumentation on the apparatus to aid the categorisation of the test result by the operator, so the installation of effective instrumentation on the test machine would be advantageous. The ability to record the tests could also be regarded as an advantage for both verification and research purposes. Other impact tests also lack instrumentation to varying degrees.

iv] There is a large background noise due to the impact of the dropweight on the sample, typically 85-100 dB(A). The human ear is quite effective in distinguishing between different frequencies and magnitudes of noise [4], but against this large background noise, 'small pops' caused by quiet or partial explosions are less likely to be easily heard than 'loud bangs' caused by complete explosions. Instrumentation that could discriminate between test events independently of noise would be helpful in corroborating noise-based assessments by the operator.

v] There are specific discrepancies between the different impact tests recognised by the UN Manual as to which explosive materials are permitted for transport, viz., the BAM test permits the transport of PETN and RDX, while the UK Rotter Test does not. This is partly due to the differing categorising criteria that each test applies, but the differing sample confinement in the tests also has some part to play and this area is currently under investigation. [5]

Development of the BAM Fallhammer Test

The problems outlined above are being addressed as follows;

a] the installation of instrumentation that can provide data which can effectively discriminate between the test categories

b] the development of a specially trained neural network that can use this acquired data to categorise the tests without the possible problems of operator subjectivity

c] the application of the developed neural network scheme to the assessment of BAM impact results from a range of explosives, including those reacting by 'decomposition'.

INSTRUMENTATION USED ON THE BAM FALLHAMMER TEST

A specially constructed logger was used to collect data from sensors around the BAM test [6]. It could take sample readings of the order of 1000 times a second, depending on the sensor. It can also handle 4 sensors simultaneously.

A program that runs on a standard 386 PC controls the data-logger, collects the data from the sensors and displays the outputs on graphs for further analysis.

In choosing the sensors, care was taken that they did not interfere with the standard BAM test procedure, i.e. did not affect the containment of the sample or the recoil of the drop-weight. This was done to ensure that if a system was developed from the research prototype, it could be applied to any BAM Fallhammer machine as an "add-on" extra.

The Microphone

The output noise of a test should give an immediate and obvious response, i.e., an 'explosion' should give a markedly more positive response than 'no reaction', especially if the microphone is adjusted to provide responses at a high noise threshold, as was the case with the microphone used in this study.

In our study the microphone was placed within the testing box of the apparatus for maximum pick-up.

The integration of the generated noise curve and the value of its peak were the initial values considered for use in the neural network. The units of these values are unimportant, as long as any required scaling is done consistently from the outset.

The microphone was used to trigger the logging of the other sensors; this saved logging time, provided consistency, and aided the comparison of results.

The Taguchi Gas Sensor

A Taguchi gas sensor was used to monitor the production of off-gases from 'explosion' and 'decomposition' events.

Taguchi sensors use a heated SnO_2 surface, the resistance of which varies in the presence of certain gases. They have a record of reliability and the recovery time of about 30 seconds is ideal for use with the BAM machine [7]. The temperature of the heated oxide surface determines the main gas that the sensor responds to. For example, sensors are available that detect CO, CH_4, H_2, and H_2S.

Although Taguchi sensors are specific, they also respond to the presence of other gases, generally with a lower voltage output. A methane sensor was employed in our study and it was operated in this general response mode to monitor the production of all the gases from 'explosion' and 'decomposition' events.

The Sound Pressure Level Meter (SPL)

A standard digital SPL meter which can give the peak noise level of the test in decibels will be used in future research to confirm the reliability of data obtained using the microphone as well as to provide an additional input to the neural network. This will also provide absolute values for the sound produced in the test that will be useful in understanding the level of discrimination required by the human ear in distinguishing relatively quiet explosions from background noise.

ARTIFICIAL NEURAL NETWORKS

A simple and convenient definition of a neural network is 'an artificial network of processors that attempts to mimic the structure of nerve cells in the human brain. It can be simulated by computer software, or in an electronic or optical form.' [8]

Neural networks are particularly effective in detecting trends or patterns in data and hence are ideal for the purposes of categorising tests.

They also have advantages over more traditionally used expert systems in that they do not require absolute data; any type of commercially available data-logger with any model of sensor will suffice, as long as the network is trained consistently from the beginning with this equipment. Complex corrections would be required to make an expert system work with a different set of sensors.

The main elements of a neural network are described in more detail as follows (see Figure 1):

a] the 'neurons' (also often called processing elements or nodes); these are points where inputs are processed to form an output. This process can be split into two parts.

i] the summation function; i inputs are summed together at the j neuron (equation 1). The bias value is a constant, specific to each neuron.

$$Y_j = \sum_i w_{ij} x_i + \theta_j \qquad (1)$$

Y_j = the output value of the neuron $\qquad$ x_i = output value of previous neuron

w_{ij} = the weight of the input connection, θ_j = the bias value specific to the neuron

i = the index of the input value j = the index of the neuron

ii] the transfer function; this function has to both *normalise* and *activate* the output value. The summed value needs to be normalised as the network program can only cope with values between 0 and 1. The transfer function also decides what the output should be. This could be a linear or non-linear response. Functions which are commonly applied are a step-function, (e.g., $Y^T_j = 1$ if $Y_j \geq 0.5$ and $Y^T_j = 0$ if $Y_j < 0.5$) or the sigmoid function (Equation 2).

$$Y_j^T = \frac{1}{1+e^{-Y_j}} \quad (2)$$

where

Y^T_j = the transformed output of the neuron j = the index of the neuron,

b] the layers; the neurons can be placed together in any sort of arrangement

c] the connections (or synapses) between the neurons

d] weights; these are values within the connections that control how much of a signal passes from one neuron to another.

e] the learning rule; i.e. the rule which determines how the neural network alters the weights so that the initial inputs produce the desired outputs.

f] the input and target data; consistent and carefully selected data are presented to the neural network, and the required solution is eventually matched to meet the target data within accepted limits by altering the weights between neurons and the bias values within neurons.

For practical applications, the type of neural network called a 'feed-forward network' employing the 'back-propagation' learning rule is used. This is the most commonly used combination of network and learning rule for categorisation problems.

As can be seen in Figure 1, in a feed-forward network the neurons in each layer are isolated from each other and are only allowed to feed the signal forward to the next layer. At least one hidden layer is required for a feed-forward neural network employing back-propagation to function properly [9], and even the most complicated problems can be dealt with by a maximum of two hidden layers.

Back-propagation means that the weighting on each connection is altered incrementally to improve the output until it reaches the desired target.

These weighting values are also a reflection on how important a connection might be i.e., the larger the weighting, the more important the connection.

The Software Package Employed

The package called NeuDesk, version 1.0 was used in this study [10] ; it operates within Microsoft Windows and has a spreadsheet format which is compatible with other spreadsheets, such as Quattro Pro and Excel.

The package is 'user-friendly' and has a selection of other learning rule algorithms and network design options to optimise its performance.

All inputs have to be in the range of 0 ± 1 and outputs in the range of 0-1; there is an automatic scaling function available for the input data to make scaling simple.

The Structure of the Network

In this development application it was also apparent that the outputs from different sensors might have to be incorporated into the network at varying stages, and that some sensors may prove ineffective, so it was decided that each sensor should have its own small network and feed its results into a single decision network (see Figure 2). This would allow a sensor and its accompanying network to be removed from the others if necessary, and would only require minor modification to the 'decision network'.

Had a fully integrated network been used this would have had to be completely re-trained if the results from a given sensor proved to be inappropriate and the related sensor inputs on the network had to be removed.

The Training Procedure

Choosing the correct data for training the network and systematically interrogating it is the most sensitive part of the process; inaccurate or unrepresentative data can make a network function inappropriately. There is also the danger of over-training. This leads a neural network to model noise in the data and so causes it to pass its point of optimum generality.

For the output of the network to have relevance, values must be assigned for each category. There are two ways of doing this.

[1] a single output, with 'no reaction' = 0 - 0.2

'decomposition' = 0.4 - 0.6

'explosion' = 0.8 - 1

[2] three different outputs, one for each category, with the largest value being the final decision.

The first option has been chosen initially for its simplicity (see Figure 2), but if there are complications in training this type of network effectively, the second option, which would incorporate more connections in a network, will be examined.

In order to train the network, each BAM test category has to be reproducible. This is not a problem for 'no reaction' or 'explosion' tests, but it is for the 'decomposition' outcome, since it is a relatively uncommon event. Initially, five 'decompositions' were used to train the network and check its applicability to the task of categorisation. A further five 'decompositions' were used to test the validity of the neural network assigned to each sensor. For more involved and complex classification problems, more sets of training data would be required.

DEFINITIONS

Implications for the BAM Definition of 'Decomposition'

The problems outlined earlier highlight the possibility that a minor event that could be included in the 'decomposition' category may be missed and be recorded as a 'no reaction'. For this reason alone, instrumentation on the BAM test should be used more extensively to confirm, or otherwise, the decision resulting from just the use of the senses of the operator.

It is hoped that different types of instrumentation will be tested on the apparatus in the near future, such as an ionisation sensing unit (ISU) which will detect the presence of the ionised gases produced by an 'explosion'.

It is also important to state that, as the criteria stand at present, a recorded 'decomposition' does not affect the measurement of the LIE value [2], i.e. it is treated like a 'no reaction' rather than an 'explosion'. It may be important to be able to identify those conditions where there is a degree of reaction without 'explosion' since the BAM impact test is being applied to assess situations much wider than transport.

The Detection of 'Decomposition'

In order for a test result to fall into this category it must not be heard by the operator, and will only be discovered on opening the sample containment. Initially, detection would be by the presence of an odour, or discolouration of the sample. A decision tree that illustrates operator choice in deciding the different types of event which can result is shown in Figure 3.

RESULTS

The Explosives

A database of instrument outputs from explosive tests recorded with full instrumentation has to be compiled for the successful training of the neural network. In particular, the reliable production and detection of 'decomposition' was necessary. As 'decomposition' is a relatively rare occurrence, the initial round of testing concentrated on those explosives that could produce such a result. Communications with expert testers suggested that certain pyrotechnics, propellants and plastic explosives were particularly prone to showing 'decomposition' results. Examples are Waterfall composition, Roman Candle composition, Tetryl, and the propellant Olin. These will be examined later in this research study.

There is also a possibility that some types of 'decomposition' might be different and verification of the analysis system with as many different 'decomposition'- producing explosives as possible will be necessary.

Other explosives were used to provide the more typical 'no reaction' and 'explosion' results. Of particular interest were 'explosion' events that were discernible to an experienced operator.

Analysis of Explosive Testing

Some typical initial test results and the accompanying data from the instrumentation are shown in Table 1.

TABLE 1
Typical Results Given By The Taguchi Methane Gas Sensor

Explosive	Category	Impact Energy/J	Recorded Output from the Taguchi Sensor		
			Area	Max. Value	Value at 4.99s
PBX (TNT-based)	N	20	0	0	0
Propellant (nitro cellulose based)	D	10	7.16	0.93	1.37
RDX/TNT	E	4	49.93	10	9.85

N = 'no reaction' D = 'decomposition' E = 'explosion'

A comparison of typical read-outs from two of the sensors installed so far (the microphone and Taguchi methane sensor) are shown in Figure 4. It can be seen that each test category produces a distinctly different display. This indicates that neural networks have the potential to discriminate between the different test categories.

The parameters shown in the last three columns of Table 1 would be fed directly into the inputs of the network. Any parameters that seem suitable for training the network can be used. In particular, the difference in outputs between an 'explosion' and a 'decomposition' have to be identified and parameters chosen to distinguish between the categories, e.g. the shape of the output graph might be different between the two cases and so the gradient and area under the graph is used in the network. Currently, training of the sensor networks is underway while further testing data are being collated.

CONCLUSIONS

The Viability of a Neural Network

In recent years there has been a great amount of interest shown in the possible application of neural networks to problems that conventional approaches have been unable to cope with, ranging from speech recognition [11] to handwriting recognition [12]. The plan outlined to train a small network to discriminate between the three impact test categories should not present difficulties, as long as the training data are carefully selected.

The Viability of the Instrumentation

The instrumentation used to date has proved to be reliable and capable of detecting 'decomposition' events that an operator would have missed, particularly with the relevant safety procedures in place, i.e. the extraction fan and the wearing of ear protection by the operator. Examination of the viability of the ISU together with other types of gas sensors will provide a range of sensors that can provide potential data for the neural network.

The readings of the SPL meter will corroborate the findings from the microphone data.

Final Objective

The ultimate goal of the project is to be able to define how many impact tests are required to train the network and how many will be required to interrogate it to confirm its effectiveness. Different BAM test machines could have their own instrumentation systems and accompanying neural networks for categorising the outcome of impact tests, and an aim of the research is to provide a basis for achieving consistency between test sites thus bringing objectivity to the test categorisation process.

The interrogation of a network with data collected from the sensors is complete within a second, and so a neural network can give an impact test operator an accurate "real-time" decision on the outcome of a test.

The on-going research will also provide data to enable the definition and role of 'decomposition' to be re-examined.

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FIGURE 1: The Main Elements of a Neural Network

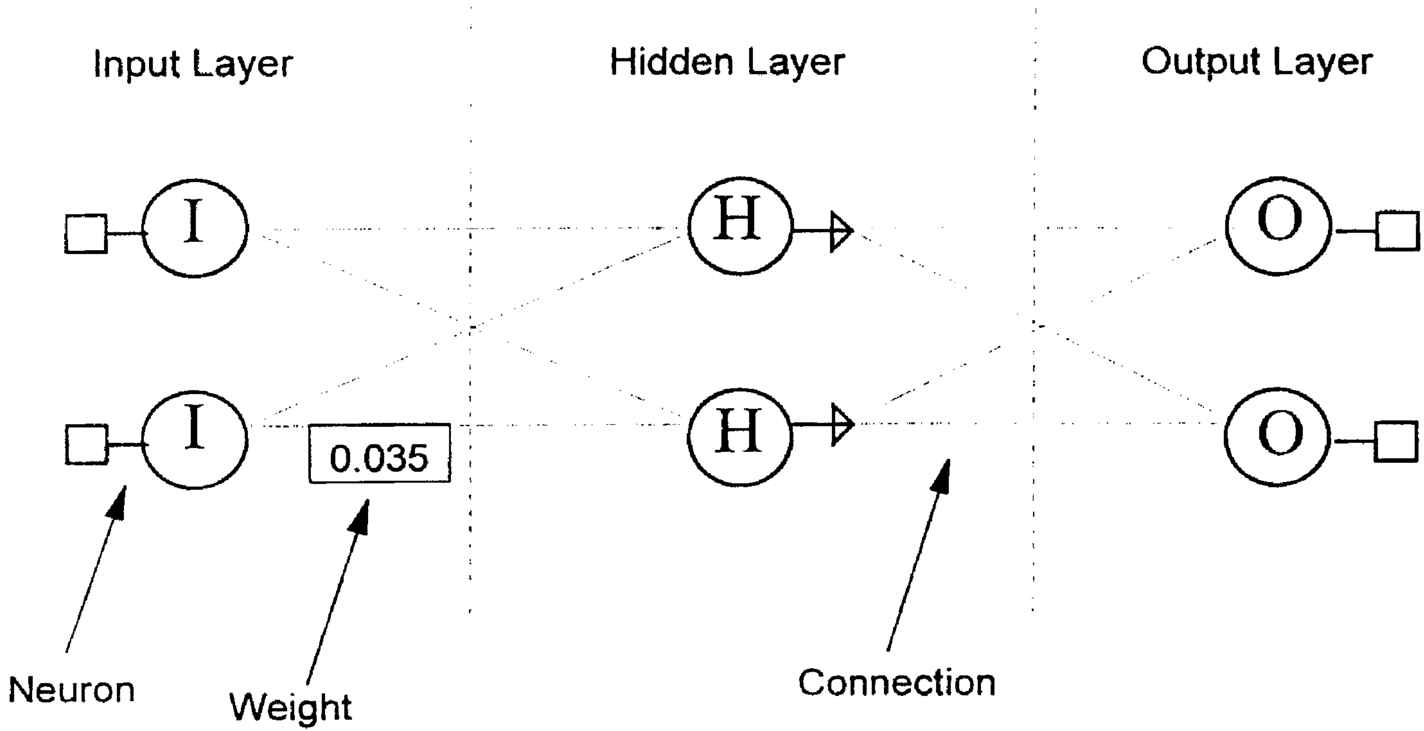


FIGURE 2: The Chosen Structure for the Neural Network

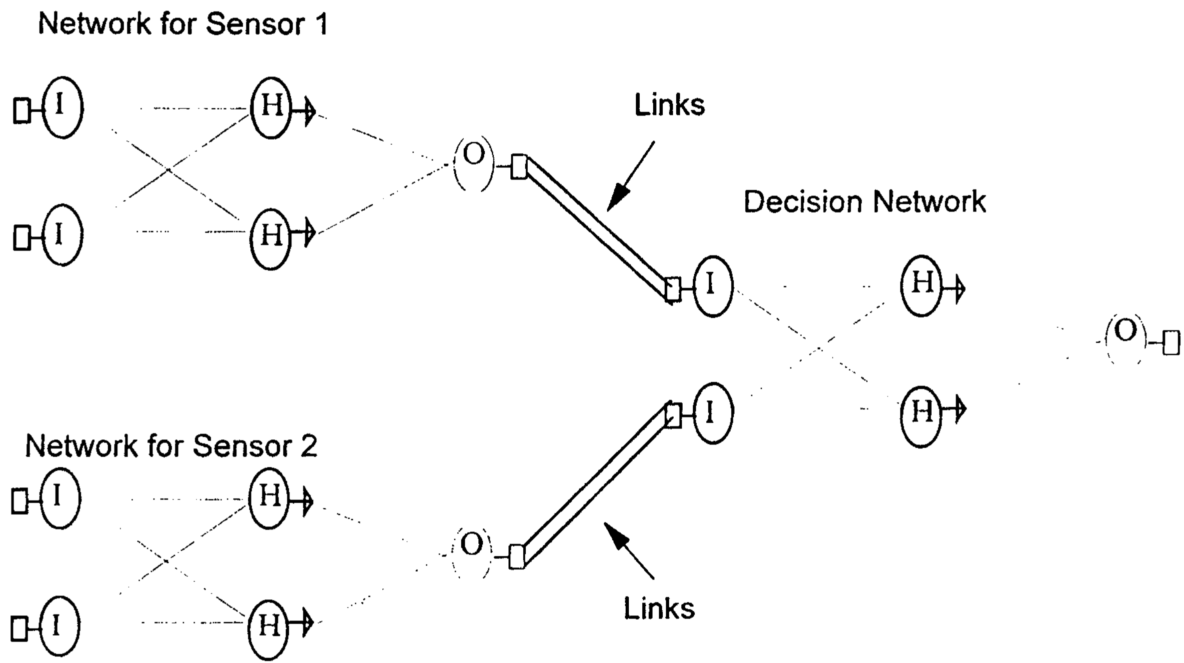
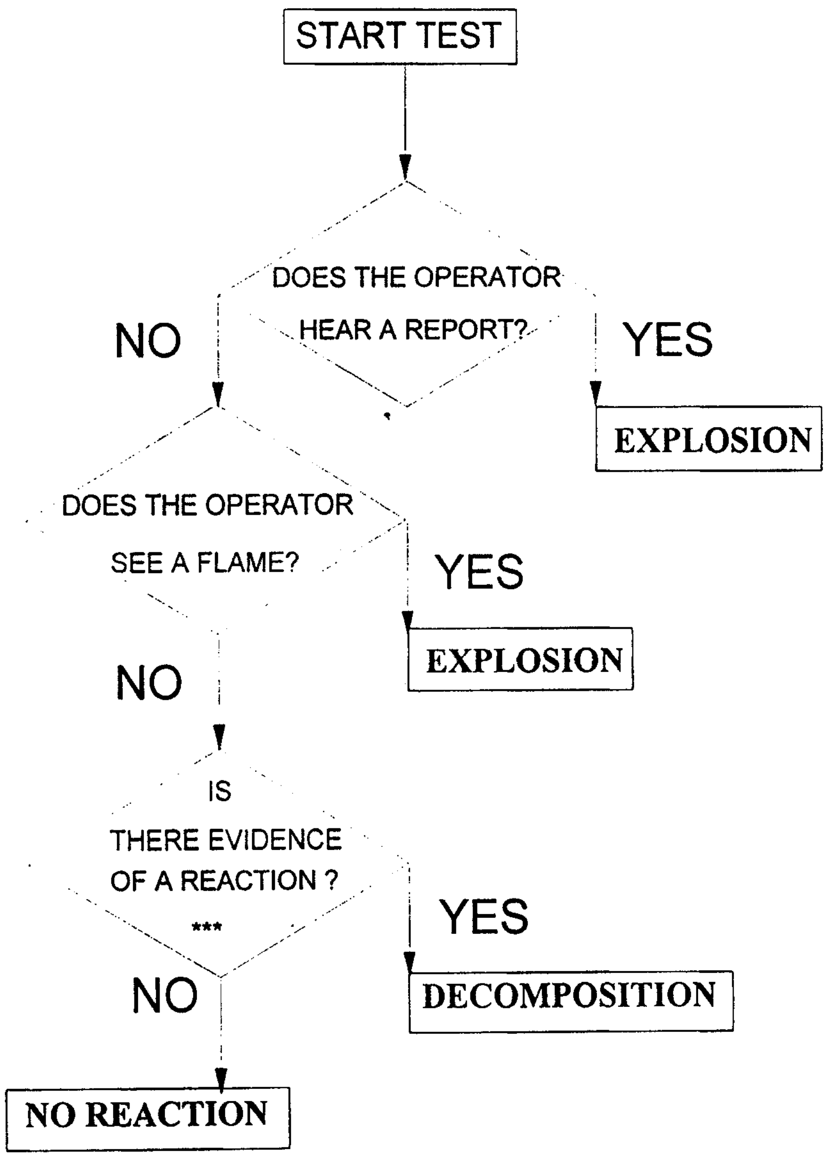
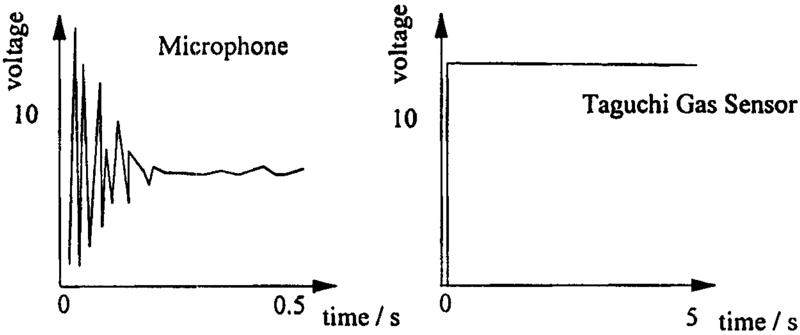


FIGURE 3: The Decision Tree for a BAM Fallhammer Operator

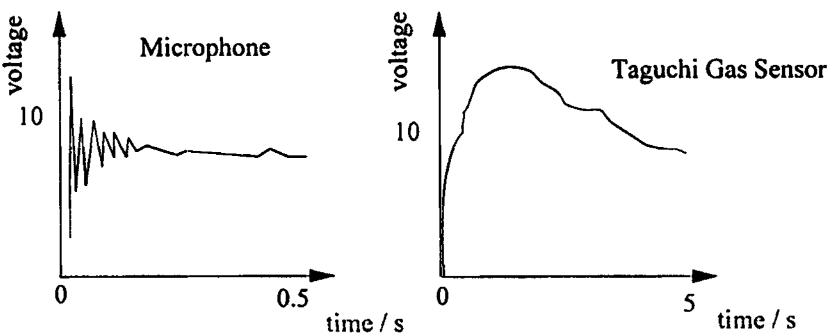


*** = odour or discolouration of material

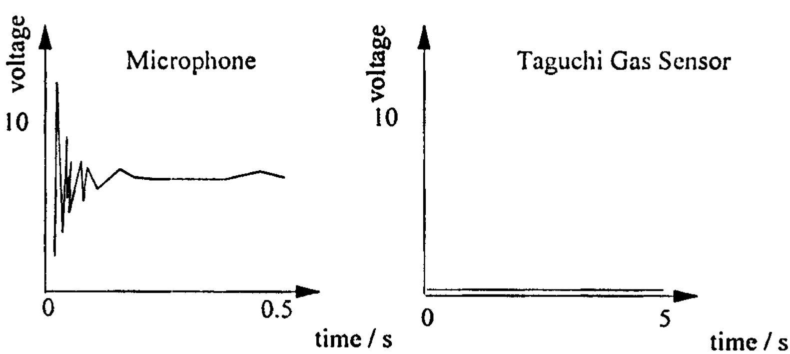
FIGURE 4: Typical Outputs Produced by the Sensors for Each Test Category



Explosion



Decomposition



No Reaction